Metacognitive Self-Regulation, Peer Learning And Interns’ Teaching Performance In Mathematics

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Abstract: This study intended to find out a mathematical model that best describes the relationship a) between teaching performance and metacognitive self-regulation, b) between teaching performance and peer learning, and c) among interns’ mathematics teaching performance, metacognitive self-regulation and peer learning. Primary data from 32 randomly selected student interns were gathered using a 15-item 7-point Likert-type questionnaire adapted from the metacognitive self-regulation and peer learning subscales of the Motivated Strategies for Learning Questionnaire (MSLQ) by Garcia and Pintrich [3] with Cronbach alphas of 0.79 and 0.76, respectively. These data were analyzed using artificial intelligence using a free trial version of a symbolic regression software. Results showed that at varying levels of metacognitive self-regulation or peer learning, teaching performance also varies. But, for maximum teaching performance, a high level of metacognitive self-regulation or peer learning, teaching performance varies. Thus, teaching performance in mathematics is greatly affected by metacognitive self-regulation. The development of metacognitive self-regulation strategies prior to entering the internship phase will definitely help an intern improve his/her teaching performance in math.

Keywords: Metacognitive self-regulation, Peer learning, Teaching Performance

1. Introduction
Among teaching interns, it is an obvious reality that some perform better over others in the teaching of Mathematics. A lot of factors can contribute to teaching performance and their differences – general academic ability and intelligence, subject matter knowledge, knowledge of teaching and learning [4], teaching anxiety and self-efficacy beliefs [10]. It is not sufficient to learn how to teach because teachers also need to learn how to learn [11]. Thus, the learning strategies of teaching interns as factors of their teaching performance are being considered in this study. Learning strategies include rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, time and study environment management, effort regulation, peer learning and help-seeking [3]. Of these learning strategies, this study focuses on the interns’ metacognitive self-regulation and peer learning strategies that can be predictive of their teaching performance. Metacognition, according to Cleary and Zimmerman [3], entails a student’s ability to choose, modify and reflect on the effectiveness of their learning strategies. It is but one aspect of self-regulated learning. As to how metacognitive self-regulation ability can be translated in their teaching performance has yet to be ascertained. On the other hand, peer learning involves the interns in explaining their ideas to others and participating in activities in which they can learn from their peers [2]. In this study, the “peers” refer to the other teaching interns who share the similar situation. Furthermore, metacognition, considered as a deeper processing strategy, was found out to improve academic achievement [6]. Results from a previous study however show that peer learning does not have significant impact on the academic performance of interns [6]. But in a much recent study, it has been found out that interns who engage in peer learning actually perform better academically [9]. Thus, this study takes on a new stance as it seeks to know how these two learning strategies can influence the teaching performance of interns. While researches abound on exploring the impact of IQ, content and pedagogical content knowledge, self-efficacy and even mathematics anxiety in the teaching of Mathematics among interns, this study aims to discover how metacognitive self-regulation and peer learning as their learning strategies can foretell their teaching performance as interns. Specifically, this study intends to answer the question: What mathematical model best describes the relationship a) between teaching performance and metacognitive self-regulation, b) between teaching performance and peer learning, and c) among interns’ mathematics teaching performance, metacognitive self-regulation and peer learning?

2. Conceptual Framework
Metacognition, in educational literature and as one facet of self-regulated learning, means “thinking about one’s thinking”. That is, every time a learner thinks or speaks about something, he/she thinks first about the possible implications and/or effects of these. Tzohar-Rozen and Kramarski [11] posits that metacognition enables learners to plan and allocate resources, monitor their own knowledge and skill levels, and evaluate their own learning levels at different points during learning acquisition. This means that a learner who has developed metacognitive skills is able to monitor and evaluate his/her learning level at different stages during learning acquisition. Researches have investigated pre-service teachers’ metacognitive strategies in terms of epistemological beliefs and metacognitive strategy use [7], and understanding of metacognitive reading strategies [8]. However, these researches have focused on the pre-service teachers’ learning experience prior to the internship phase. The internship program however poses a different challenge to pre-service teachers as it involves a continuous learning process where a teaching intern can learn, re-learn, and unlearn certain concepts from previous and current courses. In the internship phase, the intern is expected to apply all the knowledge and skills learned in previous courses. Peer learning, as a self-regulatory strategy, has been defined as the use of study groups or friends to help an individual learn [6]. This self-regulatory strategy is considered as a subscale of Resource Management strategies. Ergen and Kanadli [5] found out that self-regulation learning strategies collectively have a big effect on the mathematics achievement of interns. However, there meta-analysis did not mention of a subscale’s effect on achievement in the same subject area or
any either course that was considered in their analysis. As shown in Figure 1, interns’ metacognitive self-regulation affects their teaching performance as they are in control of how they learn and use this learning in their demonstration. Moreover, as they self-regulate, their ability to learn through others either by peer learning is affected i.e. their knowledge of what they need in order to have a good teaching performance dictates whether they will seek help or learn from others.

As shown in Figure 2, the software shows a range of solutions or models with “Fit” (accuracy of model) and “Size” (complexity of model) indices on the top left portion. This allowed researchers to choose an appropriate solution and compare it with the R² Goodness-of-Fit and correlation coefficient. The higher the R² value, the closer is the predicted model to the actual data points. Although the software showed correlation coefficients for each model, these coefficients though cannot be used to interpret the model whose graph shows a non-linear relation among the variables. Hence, in the case of this research, the mean absolute error was considered in the selection of the “most” appropriate mathematical model. The upper right corner of the screen shows the plot of the predicted model and the data points. Below it is a Pareto chart showing the error/complexity ratio and the model, the higher the ratio, the higher the error of the chosen model. However, if the ratio is closer to 0, then the model becomes more complex. Thus, in choosing a model, a balance between error and complexity must be considered.

4. Results and Discussion

Teaching Performance and Metacognitive Self-regulation

Interns’ teaching performance \( w \) and metacognitive self-regulation \( x \), can be modeled by the following equation:

\[
 w(x) = 8.14 + 0.40\cos x - \sin(1.16 + 0.12x^{0.45}\sin(x)) \quad \text{(Equation 1)}
\]

Figure 3. Teaching performance and metacognitive self-regulation: (a) observed vs. predicted plot, (b) solution fit plot, and (c) error/complexity or Pareto chart
Equation 1. \( w(x) = 8.14 + 0.40 \cos x - \sin(1.16 + 0.12x^{0.45} \sin x) \), was chosen among others since it has a mean absolute error of 0.57. This means that at each point of the model, the actual data is 0.57 units away. The Pareto chart in Figure 3c shows that the chosen model is right in the middle of all the models generated by the program. Thus, the chosen model is a balance between complexity and accuracy. This indicates how close the model describes the actual data. The variable sensitivity, that can be accessed in the report and analysis tools of the software, of 45% expresses how sensitive one variable is affected when the other variable changes. In this case, as the level of metacognitive self-regulation changes, the teaching performance of the intern is sensitive to change by just 45%. The resulting equation yields the sine and cosine functions which by nature are represented by sinusoidal curves. This goes to show that at some values of \( x \), the value of \( w \) may correspond to a low or high point in the graph. This implies that at different levels of metacognitive self-regulation of the teaching interns, their teaching performances also vary. Metacognitive self-regulation strategies, as reflected in the research instrument, include making questions for focused reading, focus on reading, changing the way he/she thinks, skimming, and changing the way he/she studies. This is attributable to the fact that there are many other factors that affect teaching performance such as academic performance, IQ, subject matter knowledge, knowledge of teaching and learning [4], teaching anxiety and self-efficacy beliefs [10]. It must be noted that the graph provided by the software graphs interns’ average performance with respect to the score obtained by a participant. Thus, the horizontal axis refers to the participant in this study. Suppose the given function \( w(x) \) is decomposed into functions \( g(x) = 8.14 \), \( f(x) = 0.40 \cos x \), and \( h(x) = -\sin(1.16 + 0.12x^{0.45} \sin x) \). Figure 4 shows the graph of \( f(x) \) and \( h(x) \) using GeoGebra. Purposely, the researchers did not graph \( g(x) \) as its effect on the overall equation is a vertical shift going up. As the constant in the equation, \( g(x) \) is the performance rating of the student when the factors \( f(x) \) and \( h(x) \) tend to zero i.e. the performance rating of the student assuming the absence of metacognitive self-regulation. However, metacognitive self-regulation will never be zero as interns are aware of how they think no matter how little. Metacognitive self-regulation skills such as skimming before actual reading, changing of study habits to improve learning, focusing on reading, and change of thinking processes are always present whether fully shown or in traces. Shown in figure 4 is the oscillating behavior of \( h(x) \) that starts when \( x \geq 3 \), this means that at a metacognitive self-regulation greater than or equal to 3, the performance rating of the student begins to oscillate with a cycle between 0.5 to 0.7.

The cycle shown in the previous figure means that the performance rating of interns repeats every 0.5 to 0.7 change in metacognitive self-regulation level.

### Teaching Performance and Peer Learning

Interns’ teaching performance \( w \), and peer learning \( y \) can be modeled by the following equation:

\[
w = 8.35 \cos(2.33 - 24.09 \cos(-1.13y))
\]

(Equation 2)

With mean absolute error of 0.65, equation 2 \( w = 8.35 - \cos(2.33 - 24.09 \cos(-1.13y)) \), models the relationship between teaching performance and peer learning. The Pareto chart in figure 5c shows that the chosen model is somewhere in the middle of all the models generated by the software. Thus, the model is a balance between accuracy and complexity. As the level of peer learning changes, the teaching performance of the interns is sensitive to change by 55%. The resulting equation is a cosine function which is a sinusoidal function with period \( \frac{2\pi}{1.13} \). This means that one cycle of observations involving peer learning and performance rating is completed from \( x = 0 \) to \( x = 5.56 \). Thus, performance rating of a group of students lie between peer learning levels of 0 to 5.56. Like in the previous graph, at some values of \( y \), the value of \( w \) may be a point anywhere in the graph. Hence, at varying levels of peer learning, the interns’ teaching performances also differ. This is due to other factors to be considered as far as teaching performance is concerned. Shown in Figure 6 is the graph of \( w = 8.35 - \cos(2.33 - 24.09 \cos(-1.13y)) \) showing the recurring pattern every 5.56 peer learning score. Moreover, the graph shows that no matter how high the peer learning score of an intern, the highest performance rating he/she can get is 9.35 or a grade of 1.5 that is described as “Outstanding”. This implies that even if the intern tries to seek help from another intern or from the instructor, his/her rating is still dependent on actual performance. The lowest rating that an intern can get is 7.35 or a grade of 2.1 that is “Satisfactory”.

**Figure 4.** Graph of \( f(x) = 0.40 \cos x \) and \( h(x) = -\sin(1.16 + 0.12x^{0.45} \sin x) \)

**Figure 6.** Graph of \( w(y) = 8.35 - \cos(2.33 - 24.09 \cos(-1.13y)) \)
Teaching Performance, Metacognitive Self-regulation, and Peer Learning

Interns’ teaching performance \( w \), metacognitive self-regulation \( x \), and peer learning \( y \) can be modeled by the following equation:

\[ w = 10.0 + \frac{-1.91y}{x} + (0.08y - 0.37) \csc (xy) \]  

(Equation 3) With a mean absolute error of 0.60, the model closely represents actual data from the questionnaire. Each point in the model is 0.60 units away from the actual data points. This means that much of the variance from the dataset can be explained by this model. Moreover, the Pareto chart shown in Figure 7c shows that the chosen model is just right in the middle of all solutions created by the software. This means that the model is close to the actual values but not as complex as the other models.

The observed versus predicted plot shown in Figure 5a are slightly close to each other except for a point between 6 and 6.5. This means that the model can predict with certain accuracy an interns’ teaching performance based on his/her metacognitive self-regulation and peer learning levels. Figure 5b shows the solution plot of the chosen model. A sharp drop in data value can be observed after the 20\(^{th}\) observation although most of the data values are close to the model. Using the software’s variable sensitivity report tool, any change in the \( x \) variable, i.e. metacognitive self-regulation level, will result in a 50% chance of increase or decrease in the teaching performance of interns. Knowledge of one’s thinking gives the intern an awareness of whether he/she is on the right track in terms of performance in math. The intern’s response is solely up to him/her. The same tool also shows that an increase in the \( y \) variable or peer learning strategies level will result in an 82% likelihood of a decrease in the intern’s teaching performance in math. Equation 3 also shows that in the absence of correction factors \( \frac{-1.91y}{x} \) and \((0.08y - 0.37) \csc (xy)\), the performance rating of the intern would be a perfect 10 or a grade of 1.0. However, student interns’ performance is rarely perfect thus the correction factors are taken into consideration in terms of metacognitive self-regulation skills and peer learning. This is validated in Table 1.

![Figure 7: Teaching performance and metacognition: (a) observed vs. predicted plot, (b) solution fit plot, and (c) error/complexity or Pareto chart](image)

Values for \( x \) and \( y \) are based on the possible scores that an intern can get from the research instrument. This shows that a low metacognitive self-regulation skill level \((x = 1)\) and a high peer learning level \((y = 7)\) will yield a negative performance rating. This means that a high peer learning level, which equates to too much interaction and dependence on peers, is not a good way to get a considerably high-performance rating. Moreover, metacognitive self-regulation skills can contribute greatly to the attainment of a high-performance rating. The mathematical models suggest that there is a relationship among interns’ teaching performance, metacognitive self-regulation strategies and peer learning. Between teaching performance and metacognitive self-regulation strategies and between teaching performance and peer learning, the trigonometric functions show that at varying levels of the variables under study, teaching performance also varies. Two teaching interns may have different levels of metacognitive self-regulation or peer learning strategies but have the same teaching performance. On the other hand, when the three variables come into play, the mathematical model reveals that at a high level of metacognitive self-regulation strategy and coupled with low peer learning strategy, teaching performance is high. This happens because when a teaching intern has high metacognitive self-regulation strategy, he is able to direct his attention towards study skills that would enable him to achieve targeted learning goals. Moreover, the intern is able to focus more on the task at hand rather than engage other people in helping him achieve the task. There is less engagement with fellow interns or persons of authority when an intern is able to metacognitively self-regulate. With less engagement comes more time to do what he is tasked to do. When both metacognitive self-regulation and peer learning strategies are low, teaching performance is also low. Performance in mathematics teaching require a degree of metacognitive self-regulation strategy as it requires time for the intern to think about what he is thinking. In other words, he needs to think and reflect while solving a math problem in the preparation of a lesson and at the same time a certain degree of metacognitive self-regulation strategy while delivering a lesson in class. The intern, while doing a demonstration, is faced with varying answers from students that would require him constant changes in mindset in order to fully achieve targeted learning goals. Thus, for maximum teaching performance, a high level of metacognitive self-regulation strategy coupled with a low peer learning skill.  

### Table 1

| \( x \) | \( y \) | \( w(x, y) \) \\n|-------|-------|----------|
| 7.75747 | 1 | 1 |
| 8.38116 | 2 | 2 |
| 7.77259 | 3 | 3 |
| 8.30391 | 4 | 4 |
| 7.962 | 5 | 5 |
| 8.00487 | 6 | 6 |
| 7.92048 | 7 | 7 |
| -3.03204 | 1 | 7 |
| 4.12516 | 2 | 6 |
| 6.86304 | 3 | 5 |
| 8.30391 | 4 | 4 |
| 8.65247 | 5 | 3 |
| 9.76229 | 6 | 2 |
| 9.28887 | 7 | 1 |

The accuracy an interns’ teaching performance based on high peer learning, teaching performance and metacognition: (a) observed vs. predicted plot, (b) solution fit plot, and (c) error/complexity or Pareto chart.
level is needed. More time to think about one’s thinking and re-focusing on a particular task is much needed before and during teaching demonstration. While peer learning helps, its effects can be seen during the preparatory phase of teaching demonstration.

5. Conclusion
Teaching performance is affected both by metacognitive self-regulation and peer learning. However, it is greatly affected by metacognitive self-regulation. As Vukman and Licardo [12] points out, “metacognitive self-regulation persists as an important predictor of school achievement at all developmental levels. As teaching interns have more control over how they learn, what they learn, their emotions, motivations, and attitudes toward learning which are all parts of metacognitive self-regulation, then their teaching performance in math increases. Hence, the development of metacognitive self-regulation strategies prior to entering the internship phase helps teaching interns perform better in teaching mathematics.

References

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